Fully Convolutional Neural Networks For Remote Sensing Image Classification

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FULLY CONVOLUTIONAL NEURAL NETWORKS FOR REMOTE SENSING IMAGE CLASSIFICATION

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ABSTRACT

We propose a convolutional neural network (CNN) model for remote sensing image classification. Using CNNs provides us with a means of learning contextual features for large-scale image labeling. Our network consists of four stacked convolutional layers that downsample the image and extract relevant features. On top of these, a deconvolutional layer upsamples the data back to the initial resolution, producing a final dense image labeling. Contrary to previous frameworks, our network contains only convolution and deconvolution operations. Experiments on aerial images show that our network produces more accurate classifications in lower computational time.

Index Terms— Remote sensing images, classification, deep learning, convolutional neural networks.

1. INTRODUCTION

Image classification is a recurrent problem in remote sensing, aimed at assigning a label to every pixel of an image. Contrary to the image categorization problem (i.e., assigning an entire image to a category such as 'residential' or 'agricultural' area), we conduct a *dense* pixel-wise labeling. A challenging aspect of the dense classification problem is the design of algorithms that can deal with the large scale of remote sensing data. Besides the execution time constraints, obtaining an accurate classification is substantially more difficult when dealing with large amounts of heterogeneous data.

Most state-of-the-art dense classification approaches label every pixel individually by taking into account its spectrum and possibly some constraints with respect to its close neighbors [1]. In this work we are dealing with large-scale satellite images that do not have a large spectral resolution, making it difficult to distinguish object classes just by their spectrum. We must thus infer the class of a pixel from its context and from the shape of the surrounding objects.

Convolutional neural networks (CNNs) learn contextual features at different scales. While initially devised for image categorization [2], we show that they are also effective at dealing with the dense classification of satellite imagery.

In remote sensing, CNNs have been used to classify the pixels of hyperspectral images. Instead of convolving in the spatial domain, convolutions are performed in the 1D domain of the spectrum of each pixel [3], or in the 1D flattened spectrum vector of a group of adjacent pixels [4]. We convolve in the 2D spatial domain instead, in order to automatically infer the contextual spatial features required to classify satellite imagery. Penatti et al. [5] show that the CNNs used to recognize everyday objects generalize well to categorize remote sensing scenes. One of the biggest challenges however is to turn the categorization networks, that generate a single category for the whole scene, into dense labeling networks. In remote sensing, Mnih [6] performs dense labeling through CNNs. The typical single-output final layer was replaced by a fully-connected layer that outputs entire classification patches.

We discuss Mnih's approach next, and point out some limitations that hamper its accuracy and efficiency (Sec. 2-3). We then propose a new CNN architecture that carries out dense labeling by relying solely upon convolutional layers (Sec. 4). We show in various experiments (Sec. 5) that it outperforms the previous approaches and offers a solid framework for remote sensing image classification.

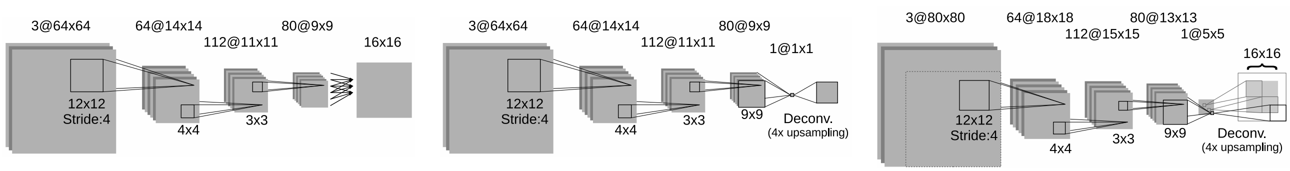
2. PATCH-BASED NETWORK

State-of-the-art CNNs for image categorization tend to follow a similar pattern: a series of convolution and subsampling operations to extract features of the image, followed by a fully connected layer to carry out the final labeling into categories. Typical CNNs produce as many outputs as number of categories, or a single output for binary labeling. For details on image categorization with CNNs we refer the reader to [7].

In our problem we must generate as output a *dense* classification, i.e., not just one categorization for the entire image, but a full pixel-wise labeling into the different categories.

To this end, Mnih proposed a patch-based convolutional neural network [6]. Given the sheer size of remote sensing images, training and inference are performed patch-wise. The network takes as input a patch of an aerial image, and generates as output a classified patch. The output patch is smaller, and centered in the input patch, to take into account the surrounding context for more accurate predictions. The way to

All Pléiades images are ©CNES (2012 and 2013), distribution Airbus DS / SpotImage. The authors would like to thank the CNES for initializing and funding the study and providing Pléiades data.



(a) Patch-based (b) Fully convolutional (c) Fully convolutional (16×16 output)

Fig. 1: Convolutional neural network architectures (e.g., "$64@14 \times 14$" means 64 feature maps of size 14×14).

create dense predictions is to increase the number of outputs of the fully connected classification layer, in order to match the size of the target patch. Fig. 1(a) illustrates such patch-based architecture. The network takes 64×64 patches (on color pansharpened images of $1m^2$ spatial resolution) and predicts 16×16 centered patches of the same resolution. Three convolutional layers learn 64, 112 and 80 convolution kernels, of 12×12, 4×4 and 3×3 spatial dimensions, respectively. The convolution kernels are three-dimensional, i.e., the two spatial dimensions plus a third dimension that goes through all the feature maps convolved.

The first convolution is not applied to every pixel of the input, but at every other forth pixel, feature referred to as a *stride*. Without strides (or other sort of subsampling) the number of parameters becomes too large for a network to learn effectively. After the three convolutional layers, a fully connected layer transforms the features into a classification map of 256 elements, matching the required 16×16 output patch.

Each convolutional layers is followed by a (ReLU) activation function [7] to add non-linearities and increase the space of functions that the network can learn. The final classification probabilities are computed by applying a sigmoid function to the output of the last layer. The loss function used for training is the cross-entropy on the sigmoid values [8].

Training is carried out by an stochastic gradient descent applied to random patches of a dataset. In every iteration, the patches are grouped into mini-batches to estimate the gradient of the loss function with respect to the network's parameters, and the parameters are updated accordingly.

3. LIMITATIONS OF THE PATCH-BASED SCHEME

We now point out some limitations of the patch-based approach discussed above, that motivate the design of an improved architecture. We first discuss the role of the fully connected layer. The size of the feature maps of its previous layer is 9×9 and have 1/4 of the resolution of the input, given the stride in the first convolution. The fully connected layer outputs a 16×16 map instead. This means that the fully connected layer does not only carry out a classification, but it also learns how to upsample the feature maps from the previous layer to the initial image resolution. In addition, the fully-connected layer allows every output to have different weights with respect to the previous feature map. For example, the activation of an output pixel at the top-left corner of the patch might not be the same as the one at the bottom-right. This makes it possible for the network to learn priors on the position inside a patch, in order to carry out the final classification. In our context, the partition of an image into patches is arbitrary, hence the "in-patch location" prior is not necessary. Otherwise, e.g., two patches that are similar but rotated by 90 degrees might yield different classification maps.

When training the patch-based network of Fig. 1a we expect that, after processing many training cases, the fully connected layer will learn a location-invariant function to classify and upsample the features of the previous layer. The experiments carried out on patch-based networks presented by Mnih [6] show the existence of discontinuities at the border of the patches in the output probability maps (see Fig. 4). This implies that the networks do not succeed in learning to classify pixels independently of their location inside the patch.

4. FULLY CONVOLUTIONAL APPROACH

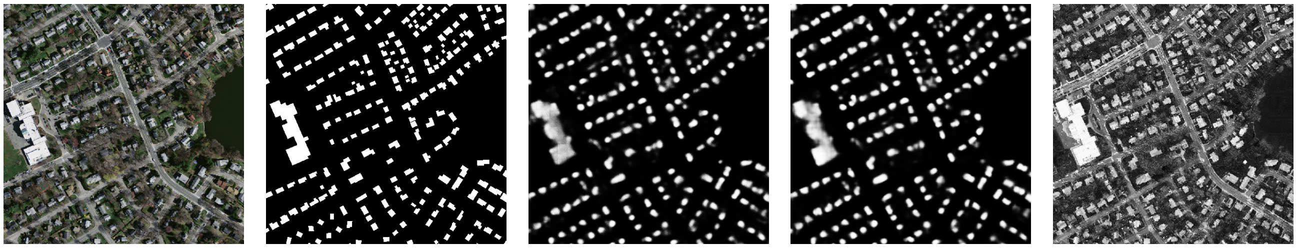
We propose a *fully convolutional* neural network architecture (FCN) to produce dense predictions. This architecture explicitly restricts the outputs of the patches to be location-independent, which means that they should be the result of a series of convolutions only.

A classification network can be "convolutionalized" [9] as follows. First, we rewrite the fully connected layer that carries out the classification as a convolutional layer. If we choose a convolution kernel whose dimensions coincide with the previous layer, the connections are equivalent to a fully connected layer. The difference now is that if we enlarge the input image, the output size is also increased, but the number of parameters remains constant. This can be seen as convolving the whole original network around a larger image to evaluate the output at different locations.

To increase the resolution of the output map, we then add a "deconvolutional" layer [9] that learns filters to upsample the resolution. A deconvolutional layer takes a single input and multiplies it by a learned filter, to produce an output patch. If these patches overlap in the output, they are simply added to create the final result. This can be seen as a convolutional layer with backward and forward passes inverted.

As compared to a patch-based approach, our fully convolutional network exhibits the following advantages:

- Elimination of discontinuities due to patch borders;
- Improved accuracy due to a simplified learning process, with a smaller number of parameters;



(a) Color image (b) Reference data (c) Patch-based fuzzy map (d) FCN fuzzy map (e) SVM fuzzy map

Fig. 2: Experimental results on a fragment of the Boston dataset.

- Lower execution time at inference, given that convolutions can enjoy the benefits of GPU processing.

We convolutionalize the patch-based network depicted by Fig. 1. We choose an existing framework to benefit from a mature architecture and to carry out a rigorous comparison.

Fig. 1b depicts such conversion into a FCN. In the patch-based network, every output inside the output patch is located at a different position with respect to its so-called *receptive field* (the portion of the input to which it is connected). This behavior is hard to justify, so we will here pretend that the output patch is of size 1×1 instead of 16×16, thus just concentrating on a single centered output. We then rewrite the fully connected layer as a convolutional layer with one feature map and with the spatial dimensions of the previous layer (9×9). Finally, we add a deconvolutional layer that upsamples its input by a factor of 4, in order to recover the input resolution. Notice that the tasks of classification and upsampling are now separated.

This new network takes as input images of different sizes, with the output size varying accordingly. During the training stage, we emulate the learning as performed by the patch-based networks by taking an input of size 80×80 in order to produce maps of size 16×16 as before (see Fig. 1c). The input patch is larger than the one of patch-based networks, not because we are dealing with more context, but because every output is now centered in its context. At inference time we take inputs of arbitrary sizes to construct classification maps. For arbitrary size of input the FCN structure is always similar, with the same number of parameters.

Fig. 1c depicts the role of deconvolution: The output value of each neuron from the previous layer is multiplied by a learned filter, which is "pasted" in the output with a stride of 4. Overlapping occurs due to the size 8×8 of the filter. The overlapping areas are added (gray) while the excess areas beyond border are excluded (white).

5. EXPERIMENTAL RESULTS

The CNNs were implemented using the Caffe deep learning framework [10]. In a first experiment we apply our approach to the Massachusetts Buildings Dataset [6]. The dataset consists of color images over Boston with $1m^2$ spatial resolution, covering an area of 340km^2 for training and 22.5km^2 for testing. The images are labeled into two-classes: building and non-building. A portion of an image with its corresponding reference is depicted in Figs. 2a-b.

We train the patch-based and fully convolutional networks (Figs. 1a and 1c respectively) for 30k stochastic gradient descent iterations on randomly sampled patches, with mini-batches of size 64, a learning rate of 0.0001, momentum 0.9 and a weight regularization of 0.0002. The parameters and rationale for selecting them are detailed by Mnih [6].

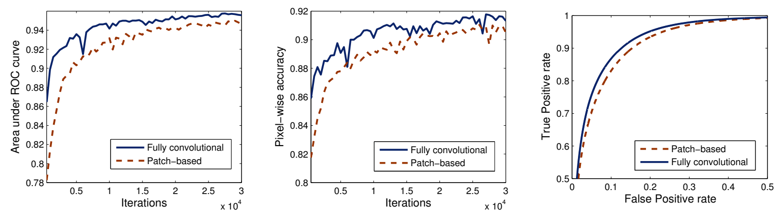
To evaluate the accuracy of the classification we used two different measures: pixel-wise accuracy (proportion of correctly classified pixels, obtained though binary classification of the output probabilities with threshold 0.5) and the area under the receiver operating characteristics (ROC) curve [11]. The latter measures the overall quality of the fuzzy maps, being 1 the area value corresponding to an ideal classifier.

Fig. 3a plots the evolution of area under ROC curve and pixel-wise accuracy, through the iterations. The FCN consistently outperforms the patch-based network. Fig. 3b shows ROC curves for the final networks after training, the FCN exhibiting a better relation between true and false positive rates (areas under ROC curves are 0.9922 for FCN and 0.9899 for the patch-based network). Fig. 2c-d depicts visual fragments.

To further evaluate the benefits of neural networks over other previous learning approaches we trained a support vector machine (SVM) with Gaussian kernel on 1k randomly selected pixels of each class. Such SVM-based approach is common for remote sensing image classification [1].

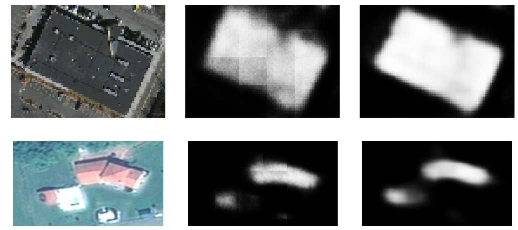
As shown by Fig. 2e, such pixel-wise SVM classification often confuses roads with buildings as their colors are similar, while neural networks better infer and separate the classes by taking into account the geometry of the context. The accuracy on the Boston test dataset is 0.6229 and its area under ROC curve is 0.5193 (lower than with CNNs, as shown in Fig.3).

In terms of efficiency the FCN also outperforms the patch-based CNN. Instead of carrying out the prediction in a small patch basis, the input of the FCN is simply increased to output larger predictions, better benefiting from the GPU parallelization of convolutions. The execution time to classify the whole Boston 22.5km^2 dataset (run on an Intel I7 CPU @ 2.7Ghz with a Quadro K3100M GPU) is **82.21s** with the patch-based



(a) Performance evolution (b) ROC curve

Fig. 3: Evaluation on the Boston test set.



Color Patch-based FCN

Fig. 4: Border discontinuities are removed through the FCN (top: Boston, bottom: Forez).

(a) Color image (b) Fuzzy map (c) Binary map

Fig. 5: Classification of a Pleiades image, with an FCN.

CNN against **8.47s** with the FCN, showing a 10x speed-up.

In a second experiment we visually demonstrate the effectiveness of FCNs for the classification of a Pleiades image covering the area of Forez, France, at a 0.5m^2 spatial resolution. We use a pansharpened color version of the image, which we train for 30k iterations on patches extracted from a subset of the surface that covers 24.75km^2. The classes and the parameters used for training are the same as for the Boston network. To preserve the amount of spatial context in this higher resolution image, we first subsample the image and then linearly upsample the output patches. The reference data used for training are extracted from OpenStreetMap project. Fig. 5 shows a test subset and its corresponding classification map. The time to infer a tile of $2.25km^2$ is 10.6 seconds for a patch-based CNN and 1.8 for the FCN.

As shown in the amplified fragments from both images (Fig. 4), the border discontinuities present in the patch-based scheme are absent in our fully convolutional setting.

6. CONCLUDING REMARKS

This work addresses the problem of remote sensing image classification with convolutional neural networks. CNNs are mostly used to categorize images, hence new architectures must be designed for dense pixel-wise classification. To this end, we proposed a *fully convolutional* neural network. By imposing the restriction that all layers must be convolutional or deconvolutional, the learning process is enhanced and the execution time reduced. Our experimental results show that such networks outperform previous approaches both in accuracy and in the computational time required for inference.

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